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Evaluation of a Multi-Agent System approach to airline disruption management

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ABSTRACT

Each day, airlines face disturbances that disrupt their carefully planned operations. Events like adverse weather conditions, sick crew members, or damaged aircraft often result in delays in the airline's schedule. An airline recovers from such disruptions through the role played by its Airline Operations Control (AOC). A Multi-Agent System (MAS) approach to airline disruption management was recently proposed under the acronym MASDIMA (Multi-Agent System for Disruption Management in AOC). The purpose of this paper is to evaluate this MAS supported AOC approach on its performance and its practical introduction. This is done using a scenario-based analysis to compare the MAS supported policy to human-team based AOC policies. A task-based analysis identifies how well AOC is able to cover a set of tasks using the MAS supported policy. The scenario-based analysis shows that the MAS supported AOC is able to find the optimal solution, and to do this significantly faster. The task-based analysis identified two main challenges for implementing the MAS supported AOC policy: i) to overcome the loss of experience that is caused by significantly automating humans roles in AOC, and ii) to reduce the workload for people that remain in AOC after its introduction. The paper concludes that implementing the MAS supported AOC policy leads to both better and faster resolutions, though the replacement of human roles also poses novel challenges that remain to be resolved: a potential increase in workload for the remaining human role and loss of experience in handling exceptional situations.

1. Introduction

Airlines constantly face disturbances that disrupt their carefully planned operations. Events like adverse weather conditions, sick crewmembers, or damaged aircraft often cause delays in the airline's schedule. Each airline has its Airline Operations Control (AOC) monitoring operations worldwide, and managing recovery from disruptions. For an airline such disruptions are very costly because they tend to cause domino effects in the highly optimized air transportation schedule. Over the year 2007 alone, U.S. carriers lost over $8 billion because of delays of some sort (Barnhart, 2009). Reducing the impact of disruptions on the airline schedule could considerably reduce these costs. Most research on the improvement of AOC decision making policy focusses on using optimization techniques for the development of decision support tools. For instance, Bratu and Barnhart (2006) propose two optimization tools that generate recovery plans for aircraft, crews, and passengers by determining which flight leg departures to postpone and which to cancel. Abdelghany et al. (2008) propose a decision-support tool that provides AOC centres with the capability to develop a proactive schedule recovery plan that integrates all flight resources. The optimization tool examines possible resource swapping and flight requoting to generate a schedule recovery that minimizes flight delays and cancellations. Petersen et al. (2012) propose a mixed-integer programming tool to solve the fully integrated airline recovery problem including the schedule, aircraft, crew, and passenger problems. In the same vein, Arikan et al. (2017) propose an optimization tool to solve the fully integrated airline recovery problem using a conic quadratic mixed integer programming formulation. Santos et al. (2017), present an integer linear programming tool to help AOC controllers decide which flights to delay and which flights to make depart on time.

From a combinatorial optimization perspective, these tools have the mathematical capability in minimizing airline operating costs and passenger costs. However, such a combinatorial optimization approach fails in capturing the complex socio-technical nature of AOC (Feigh and Pritchett, 2010; Bruce, 2011a; Richters et al., 2017). In order to address these socio-technical challenges, Castro (2013) has taken a Multi-Agent System (MAS) based approach to the development of a novel decision support tool for airline disruption management. The resulting tool is referred to as MASDIMA (MAS for Disruption Management in AOC). In order to realize a better handling of the complexity of the airline

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disruption management problem, Castro (2013) proposes replacing several human roles in AOC by software agents. The latter implies a large change in the established AOC policy that is largely depending on coordination and decision-making by a team of humans.

Inherent to the complex socio-technical nature of airline operations, it involves dynamic interactions between multiple actors, systems and uncertainties. This makes performance evaluation and comparison of a novel AOC policy far from trivial. The challenge is twofold: i) How to identify a challenging airline disruption scenario that can be used as a benchmark? and ii) How to evaluate the application of an AOC policy on a benchmark scenario. The former problem has been addressed in Bruce (2011b) as follows. Supported by three experts with extensive AOC background, Bruce (2011b) developed a challenging airline disruption scenario, while receiving critical feedback from four other AOC experts. The major roles given to the AOC experts was to ensure that the scenario was representative of realistic and sufficiently complex disruptions (Bruce, 2011b).

Bouarfa et al. (2016) have shown that the second problem, i.e. to evaluate the application of an AOC policy to a given airline disruption scenario, can be addressed using Agent-Based Modelling and Simulation (ABMS). For applications in other domains, ABMS has shown its effective use in analyzing complex socio-technical systems (Macal and North, 2010; van Dam et al., 2013). Bouarfa et al. (2016) have applied ABMS to the evaluation of the performance of four human-team AOC policies to the challenging airline disruption scenario of (Bruce, 2011b). Three of the four policies were based on current airline practice, whereas the fourth was based on joint activity coordination theory for human teams (Klein et al., 2005). For each of these four policies, Bouarfa et al. (2016) capture each human in the AOC team, including its specified role, as an agent in the ABMS. The obtained results in (Bouarfa et al., 2016) showed that the three current policies led to similar resolutions of the disruption benchmark as the best one identified in (Bruce, 2011b). However, the fourth policy led to a significantly better resolution of the benchmark disruption scenario. A key contribution of the current paper is to evaluate the MAS-supported AOC policy of Castro (2013) on the benchmark disruption scenario of Bruce (2011b), and to compare the results with those obtained by Bouarfa et al. (2016) for the other AOC policies.

The airline disruption scenario development by Bruce (2011b) was focused on human-based AOC disruption management policies. However, one should be aware that there may be airline disruption scenarios which are easier to resolve by a human team based airline disruption management policy, than it is for a MAS supported policy. In order to realize a better understanding of the specific types of scenarios where this might be an issue, the current paper also conducts an expert-based evaluation of remaining human tasks in a MAS supported AOC policy. This leads to the identification of scenarios that are potentially more critical for a MAS supported AOC policy.

This paper is organized as follows Section 2 provides background on both AOC and the agent-based paradigm Section 3 provides a summary of multi-agent coordination approaches from literature Section 4 describes the MAS supported AOC policy and its application in AOC Section 5 compares the MAS supported AOC policy versus the human coordination policies that have been studied in (Bouarfa et al., 2016). Section 6 describes an expert-based evaluation of the remaining human tasks in the MAS supported AOC policy. Finally, Section 7 presents the conclusions and recommendations of this research.

2. Background

2.1. Airline Operations Control

The idea of monitoring and controlling a transport network in real time is not new. The concept was first established in the 19th century in the railway industry, when the development of the telegraph made it possible for information to travel faster than physical transport (Peters, 2006). This allowed for a central location in which real-time information about the current status of the network could be collected and acted upon. Today, the concept of monitoring operations in real-time is used across industries, with AOC as one example.

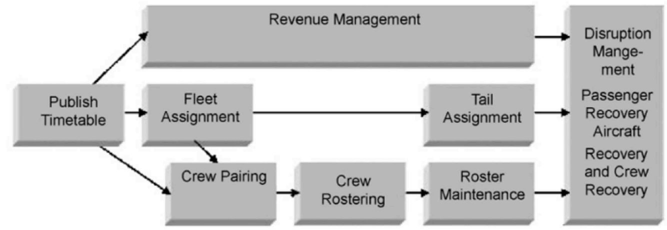

Fig. 1. Disruption management starts when airline planning ends (Kohl et al., 2007).

Airline disruption management starts when airline planning ends (Fig. 1). The scheduling process starts with publishing a preliminary timetable up to 1 year before the day of operations. The timetable provides the basis for the aircraft schedule, which assigns an aircraft type to each flight. With the flights and aircraft types known, crew pairing defines the amount and type of crew per flight. The next step is to assign specific aircraft and individual crewmembers to each flight in the tail assignment and crew rostering phase. After publishing the crew roster, crewmembers can request changes in their schedule in the roster maintenance phase. Disruption management starts after the airline planning process ends and is considered a tactical step during recovery (Grandeau, 1995; Clarke, 1998; Kohl et al., 2007; Clausen et al., 2010).

During the day of operations, the airline schedule is subject to many disruptions. The four main airline schedule disruptors are aircraft mechanical problems, severe weather, airport congestion, and industrial action (e.g. strikes). The goal of AOC is to deliver customer promise despite these disruptions. In doing so, it should minimize airline costs incurred during recovery, and return to the original schedule as soon as possible (Kohl et al., 2007).

Disruptions affect the aircraft, crew, and passenger resources of an airline. Managing these resources is the duty of AOC operators. Each AOC operator has his own role. Such roles might vary per airline, but six are common to most airlines: flight dispatch, aircraft control, crew tracking, aircraft engineering, customer service, and Air Traffic Control (ATC) coordination (Kohl et al., 2007). Because the airline operations supervisor is ultimately responsible for AOC operations (Clarke, 1998), he/she has the authority to make changes in the nominal schedule.

An airline controller can manage a disruption in many different ways. To resolve a problem that affects the aircraft resource, a flight can be delayed, cancelled, rerouted, or the aircraft exchanged. Crew related problems can also be resolved by cancelling or delaying the flight, or by calling in new crew or reassigning existing crew. To resolve a passenger problem, an operations controller might change the passenger's flight or delay the passenger (Barnhart, 2009; Castro, 2013).

How well disruptions are managed depends on how AOC is organized. For example in Europe, AOC often performs the task of flight following, while flight planning and dispatch is often performed outside AOC (Kohl et al., 2007), whereas in North America, flight dispatchers and planners are assumed to make an integral part of AOC (Pujet and Feron, 1998; Clarke, 1998; Castro and Oliveira, 2011). In the current paper we adopt the latter, which is also in line with Bruce (2011b), Castro (2013) and (Bouarfa et al., 2016).

According to Castro (2008) and Machado (2010), there are three types of AOC centers. A decision center, a hub control center, and an integrated control center. In a decision center, airline controllers are located in the same space while other functional groups such as maintenance services and crew control are located in a different physical space. A hub control center oversees the activities at the hub, which may include ground and passenger services, but other operations such as aircraft control are monitored from a different location. An